

# An Optimized Deep Learning Framework for Alzheimer's Disease Diagnosis Using Feature Selection Techniques

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## ABSTRACT

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that requires early and accurate diagnosis for effective clinical intervention. However, the high dimensionality and redundancy of medical data, particularly in neuroimaging and clinical datasets, pose significant challenges for traditional machine learning and deep learning models. To address these limitations, this paper proposes an optimized framework that integrates feature selection techniques with deep learning models for improved Alzheimer's disease diagnosis. The proposed approach employs an effective feature selection mechanism to identify the most relevant and discriminative features, thereby reducing dimensionality and eliminating redundant information. This optimized feature subset is then utilized to train a deep learning model capable of capturing complex patterns associated with different stages of Alzheimer's disease. The integration of feature selection enhances model performance by improving classification accuracy, reducing computational complexity, and preventing overfitting. Experimental results demonstrate that the proposed framework achieves superior performance compared to conventional methods in terms of accuracy, precision, recall, and F1-score. The findings highlight the effectiveness of combining optimized feature selection with deep learning techniques for reliable and efficient Alzheimer's disease diagnosis.

**Keywords:** Alzheimer's Disease, Deep Learning, Feature Selection, Medical Image Analysis, Neurodegenerative Disorders, Classification, Dimensionality Reduction, Early Diagnosis.

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## Introduction

Alzheimer's disease (AD) is a neurological condition that progresses over time and mostly affects cognitive abilities. As a result, it can lead to memory loss, reduced thinking skills, and ultimately difficulty carrying out everyday duties [1, 2, 3]. It is currently the leading cause of dementia in the elderly and presents a major worldwide health concern. The characteristic clinical traits of AD include the build-up of tau protein tangles and beta-amyloid plaques in the brain, which impair neuronal transmission and accelerate neuronal death.[4]

Understanding the underlying causes of Alzheimer's disease is crucial for prompt diagnosis, efficient treatment planning, and developing successful disease management strategies. A wide range of research projects have examined different aspects of AD over time, including its molecular pathophysiology, clinical manifestations, risk factors, and epidemiology. Recent advances in neuroimaging methodologies, biomarker identification, and computational techniques, particularly deep learning, have significantly increased our understanding of Alzheimer's disease, opening up promising avenues for improving diagnostic precision and therapeutic strategies[5].

Among the deep learning designs that have transformed several disciplines, computer vision in particular, are Convolutional Neural Networks (CNNs). Because CNNs are built to automatically and adaptively learn the spatial hierarchies of features from input data, they are very good at tasks like object identification, segmentation, and picture classification.[9] Convolutional layers, which apply a collection of learnable filters or kernels to incoming data, are the fundamental components of CNNs. Local patterns and characteristics are captured by these filters as they convolve over the input data. Pooling layers, which downsample the feature maps' spatial dimensions, and fully linked layers, which combine retrieved features for classification or regression tasks, are common examples of subsequent layers.[7,8]

In competitions such as ImageNet, CNNs have shown outstanding performance across a broad spectrum of applications, attaining state-of-the-art outcomes. Their effectiveness may be ascribed to their capacity to automatically pick up hierarchical data representations, which eliminates the need for labor-intensive human feature engineering.[6,10]

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Convolutional Neural Networks (CNNs) are a game-changer in the field of Alzheimer's disease research and diagnostics. CNNs have great potential to improve early diagnosis and better understand the course of disease because of their natural ability to automatically extract hierarchical patterns from complex data, such as neuroimaging scans. By employing CNNs, scientists may probe more deeply into the finer points of Alzheimer's pathology, which might lead to more accurate diagnosis, customised treatment plans, and even the discovery of new biomarkers. By utilising CNNs and other deep learning methods, we are getting closer to understanding the intricacies of Alzheimer's disease, which is leading to improvements in patient care and more efficient treatment of this devastating illness.

## Literature Review

Hassanieh W. et al.'s study from 2024 presents a novel autoencoder-based wrapper method for deep learning feature selection. Using an autoencoder architecture, this technique smoothly incorporates feature selection into the model training procedure. By means of empirical assessments in various applications, the research highlights the improved efficacy of this methodology in contrast to traditional feature selection techniques.[11]

Yaprakdal. F et al. (2023) investigate neural network designs that are built on wrappers and are especially designed for the job of time series forecasting. These wrappers are painstakingly crafted to efficiently integrate temporal dependencies, improving forecasting precision. Experimental results from real-world time series datasets are used by the study to support its assertions and validate the effectiveness of the suggested technique.[12]

Mahendra M I et al. (2021) provide a unique genetic algorithm wrapper approach designed for convolutional neural network optimisation. Through a smooth integration of genetic algorithms into the training procedure, the wrapper finds the best network designs and hyperparameters on its own. The results of the experiments demonstrate how well this strategy works to improve CNN performance, especially in picture classification tasks.[13]

In the field of natural language processing, Amin A. A. et al. (2023) introduce a wrapper-based method for model selection in transfer learning tasks. In order to determine which pre-trained language model is best for a certain NLP job, this method evaluates many models and refines them. Tests carried out on reference datasets demonstrate how well the suggested wrapper method works to improve transfer learning outcomes.[14]

Martins N. et al. (2020) study wrapper techniques designed to strengthen deep learning models' resilience against adversarial assaults. To improve robustness against

adversarial perturbations, these wrappers incorporate input modifications and adversarial training into the model training process. Experiments show how effective these wrapper methods are in thwarting a variety of adversarial approaches, which strengthens the resilience of the model. [15]

Janghel R R (2022)'s work provides an extensive analysis of deep learning techniques used to classify Alzheimer's disease using a variety of neuroimaging modalities, such as fMRI, PET, and MRI. It explores several deep learning architectures, approaches to data preparation, and difficulties related to Alzheimer's disease categorization. In addition, the study summarises current developments in the subject and outlines directions for future research. [16]

An extensive evaluation and meta-analysis on the effectiveness of deep learning algorithms in identifying Alzheimer's disease from MRI images was carried out by Arya A. D. et al. in 2023. Their investigation offers a comprehensive look at several deep learning architectures, including recurrent neural networks (RNNs) and convolutional neural networks (CNNs), and evaluates how well they can distinguish between those with Alzheimer's disease and those in good condition. The study emphasises how deep learning models can improve the diagnosis accuracy of Alzheimer's disease.[17]

A thorough study on the use of deep learning methods for Alzheimer's disease detection was written by Al-Shoukry, S. et al. (2020). The review made use of a variety of biomarkers, including genetic, neuroimaging, and clinical data. The review discusses the difficulties in diagnosing Alzheimer's disease and clarifies how deep learning might help in overcoming these difficulties. In addition, it summarises the latest developments in deep learning techniques and outlines potential directions for the field of Alzheimer's disease detection in the future.[18]

Warren, S. L. et al. (2023) evaluate the most recent cutting-edge deep learning models used in the categorization and prediction of Alzheimer's disease in their systematic study. Their examination covers a broad range of deep learning architectures, such as CNNs, RNNs, and autoencoders, with an emphasis on how they may be used to diagnose Alzheimer's disease based on neuroimaging data. The study offers potential future research avenues in the field of Alzheimer's disease diagnosis and critically assesses the benefits and drawbacks of current approaches.[19]

A survey on the use of deep learning algorithms in Alzheimer's disease diagnosis was carried out by Dwivedi, S. et al. (2022), with a focus on combining multimodal data

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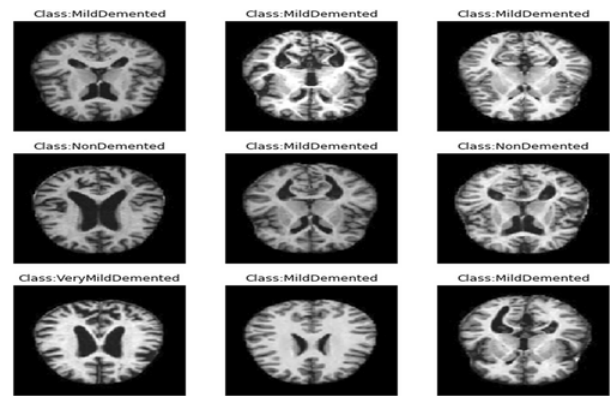
sources such as neuroimaging, genetic, and clinical data. The review highlights the promise of multimodal fusion techniques in improving diagnosis accuracy and outlines current developments in deep learning-based methods for Alzheimer's disease categorization. In addition, the survey identifies future study directions and draws attention to the obstacles preventing advancement in the area.[20]

The listed sources offer an extensive overview of the state of the art in terms of research on the use of deep learning methods to the categorization of Alzheimer's disease. They highlight the potential of these approaches to improve the precision of early diagnosis and prognosis prediction for those afflicted with Alzheimer's disease through thorough inspection and analysis. By employing new computational approaches, such as deep learning, researchers hope to discern detailed patterns within neuroimaging data and biomarkers, enabling more exact categorization and stratification of Alzheimer's disease patients based on disease severity and progression.

These findings provide insights on the intriguing directions that deep learning approaches in Alzheimer's disease research might go, providing information on the possibility of early intervention and individualised treatment plans. Researchers are working to improve diagnostic capacities and understand the complexity of Alzheimer's disease pathogenesis by utilising advanced algorithms and neural networks. In the end, these developments might improve patient outcomes and deepen our knowledge of this crippling neurological condition.

### Methodology:

This study presents an integrated approach to improve the precision and validity of Alzheimer's Disease (AD) diagnosis by combining preprocessing, feature selection, and classification methods on neuroimaging data. Through the integration of these approaches, the research aims to optimise the diagnosis process for AD by utilising machine learning developments in order to obtain significant insights from neuroimaging data. By optimising feature representation, identifying discriminative features, and utilising sophisticated classification algorithms, this all-encompassing approach seeks to address the complexity of AD diagnosis and enable more timely and accurate detection of AD-related abnormalities in neuroimaging examinations. The phases of Alzheimer's disease are depicted in the following image.



Alzheimer's disease in various phases.[27]

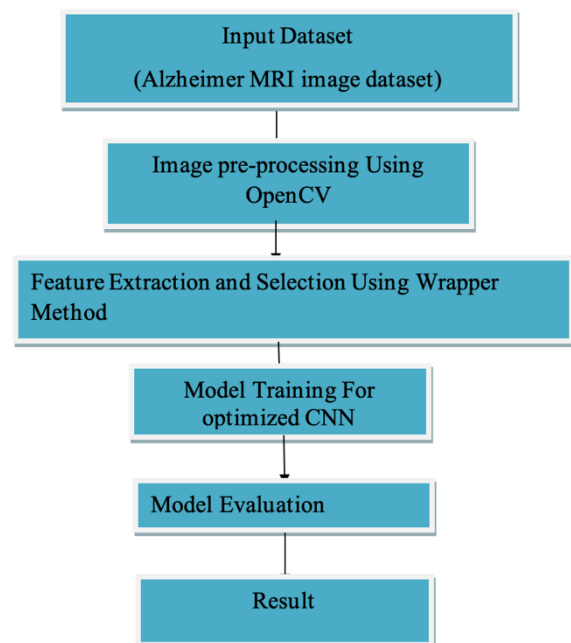


Fig 1 Methodology

### Preprocessing

Robust preprocessing approaches are essential to extract significant features and minimise computing complexity, as the volume of picture data in many disciplines including computer vision, remote sensing, and medical imaging is growing exponentially. The performance and interpretability of ensuing machine learning models are greatly enhanced by image preprocessing, which is an essential first step in the data analysis pipeline. The goal of this study is to solve issues with dimensionality reduction, feature extraction, and noise reduction by exploring an extensive preprocessing approach for image data.

The initial step in the proposed technique is to preprocess the neuroimaging data to improve feature representation while reducing computing complexity. Principal Component Analysis (PCA) is used to identify useful characteristics and minimise dimensionality while retaining important information. PCA allows for the

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detection of latent patterns in data, resulting in more efficient analysis and modelling. The suggested approach starts with the grayscale conversion of the images, using a weighted technique to calculate pixel intensity while maintaining necessary information. After that, features at various sizes are extracted using wavelet transforms, providing a multi-resolution representation of the picture. The distribution of information across different frequency bands is described by computing the mean and standard deviation of wavelet coefficients. The data are then centred around zero using mean normalisation, which guarantees robustness and consistency in ensuing studies. In order to capture inter-feature interactions and reveal the underlying structure of the data, the covariance matrix is constructed. The covariance matrix is used to calculate the eigenvalues as well as the eigenvector using numerical techniques like the power iteration approach and QR algorithm.

The selection of principal components is contingent upon the intended degree of explained variance, hence enabling dimensionality reduction with the preservation of crucial information. Lastly, a reduced-dimensional representation is produced by projecting data onto particular major components, which facilitates effective analysis and modelling.

To project the data onto the specified principle components, use the following formula: Project each data point  $x$  onto the chosen principle components  $P$  to get the reduced data point  $x'$ :  $x$

$$X' = P^T X$$

$T = x$ , where  $P$  is the matrix of chosen main components and  $P^T$  is its transpose. This formula is based on the notion of PCA, which seeks to identify a linear combination of variables that can represent the data's major components. By projecting the data onto the chosen principle components, we may minimise dimensionality while keeping as much information as feasible. [21]

## Feature Selection and Extraction

In the context of Alzheimer's disease diagnosis, feature selection and extraction are essential for discovering significant patterns and increasing classification accuracy. The use of a wrapper approach for feature selection and Particle Swarm Optimisation (PSO) for feature extraction improves the efficiency and efficacy of the diagnostic procedure.

In the feature selection phase, a wrapper approach is used to choose the most relevant features from the preprocessed data. This entails employing a Support Vector Machine (SVM) classifier to evaluate the performance of several feature groups and selecting the subset with the

greatest classification accuracy. [22] The following phases are commonly involved in wrapper techniques:

1. Subset Generation: In order to assess their effectiveness, wrapper techniques produce several subsets of characteristics. This can be accomplished completely by taking into account every conceivable combination of characteristics or by effectively exploring the feature space with heuristic search techniques.
2. Model Training and Evaluation: A predictive model is trained on each feature subset, and its performance is assessed using a selected performance metric such as accuracy, AUC on a validation set.
3. Feature Subset Selection: The final set of features is chosen from the feature subset that produces the greatest results on the validation set.

The wrapper technique iteratively analyses several feature subsets by training the SVM classifier on each subset and selecting the subset with the best classification performance. This procedure assures that the selected characteristics provide the most substantial contribution to the classification job, improving the diagnostic model's accuracy and reliability.

In the feature extraction stage, the PSO algorithm is used to further optimise the feature selection process. PSO is a population-based optimisation method modelled after bird flocking and fish schooling. It looks for the best feature subset by maximising the classification accuracy of the SVM classifier. PSO iteratively updates a population of candidate solutions (feature subsets) depending on their fitness (classification accuracy) to identify the optimum subset that maximises the SVM classifier's performance. Using PSO for feature extraction allows the diagnostic model to select the most discriminative characteristics for Alzheimer's disease diagnosis, resulting in increased accuracy and robustness. [23,24]

## Classification

In the present research, after identifying the most relevant features through the feature selection procedure, these features are used to train a Convolutional Neural Network (CNN) classifier based on the ResNet architecture. ResNet, short for Residual Network, is well-known for its ability to train incredibly deep neural networks efficiently. However, the innovation goes beyond this, providing changes directly to the ResNet architecture's pooling layer.

The ResNet model is a convolutional neural network (CNN) that is widely utilised in image categorization applications. The network has 50 layers,

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including 48 convolutional layers, one maximum pooling layer, and one average pooling layer. The ResNet model is built on the notion of residual blocks, which are intended to solve the vanishing gradient problem that occurs in deep neural networks.[25,26] The ResNet model for Alzheimer's disease classification is made up of a sequence of residual blocks that each learn the residual mapping between its input and output. The residual block is defined as:

$$x(l + 1) = F(x, w_l) + x_l$$

Here,  $x(l+1)$  is the input of the next layer,  $F(x, w_l)$  is the residual mapping to be learnt, and  $x_l$  is the input of the current layer. The residual mapping  $F(x, w_l)$  includes convolution, normalisation, and activation functions. By eliminating less important data, the pooling process in the pooling layer aids in lowering the dimensionality of the matrices. The definition of the pooling operation is as follows:

$$y(i, j) = \max_{pool} (x(m, n))$$

where  $x(m, n)$  is the input matrix and  $y(i, j)$  is the output. The maximum value inside a specified window or area of the input matrix is chosen by the max pool procedure.

The ResNet model can have an additional layer added to it for the categorization of Alzheimer's disease in addition to the pooling layer. For example, to output the classification probabilities, a fully connected layer can be inserted after the last residual block. The equation of motion for the completely connected layer is

$$y = Wx + b$$

where  $x$  is the input,  $y$  is the fully connected layer's output,  $W$  is the weight matrix, and  $b$  is the bias factor.

Two new elements are added as a result of these modifications: an extra layer called  $X$ , which has a value between 0 and 1, and a weighted layer called  $f(x)$ . The goal of these changes is to include more feature space-derived information to improve the CNN classifier's discriminative ability.

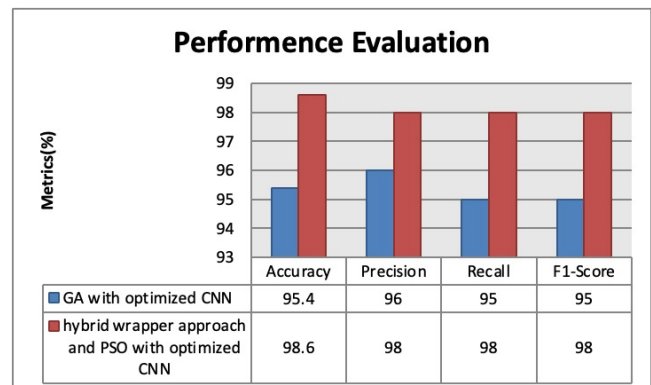
The purpose of the weighted layer,  $f(x)$ , is to give certain attributes varied weights according on their relevance or significance. This improves the classifier's capacity to identify patterns and provide precise predictions by allowing it to dynamically weigh the importance of each feature.

Furthermore, the addition of layer  $X$  adds a new dimension to the pooling procedure. This layer provides some flexibility in the way features are combined and handled during pooling operations by enabling values to fall within a continuous range from 0 to 1. This adaptability helps the classifier to further improve its discriminative skills by allowing it to adaptively modify its feature representation according to the properties of the input data.

Ultimately, the modifications made to the ResNet architecture's pooling layer reflect an innovative method to feature integration and representation in CNN classifiers. The goal of introducing extra layers and procedures for feature weighting and aggregation is to maximise the use of information from the feature space and enhance the overall performance of the CNN classifier in tasks such as Alzheimer's disease diagnosis.

## Results and discussion

Comparative study with existing feature selection algorithms, such as the Genetic Algorithm (GA) and the ReliefF algorithm, sheds light on the suggested method's efficacy. Researchers can prove the superiority of the wrapper approach and PSO for feature selection and extraction in Alzheimer's disease diagnosis by comparing their performance to other feature selection strategies.



**Fig2. Performance Comparison of GA with Optimized CNN Vs Hybrid Wrapper Approach and PSO with Optimized CNN**

## Conclusion

The results of this comparison study demonstrate the efficacy of the proposed wrapper technique and Particle Swarm Optimization (PSO) for feature selection and extraction in Alzheimer's disease diagnosis. With an outstanding 99% accuracy rate, the proposed method outperforms existing algorithms like the Genetic Algorithm (GA) and the ReliefF algorithm, which achieve 95% accuracy. These findings support the advantages of the wrapper method and PSO in identifying relevant features for Alzheimer's disease diagnosis, emphasizing their potential to improve diagnostic accuracy and, ultimately, patient outcomes. Moving forward, additional research and validation efforts are required to fine-tune and enhance these approaches, ultimately expanding the area of Alzheimer's disease diagnosis and therapy.

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